Flexible Domain Adaptation for Multimedia Indexing

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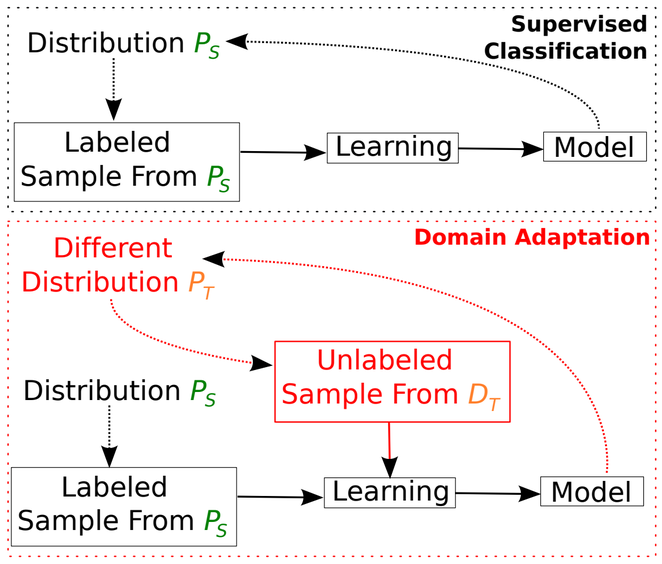
Introduction, Notations and Motivation

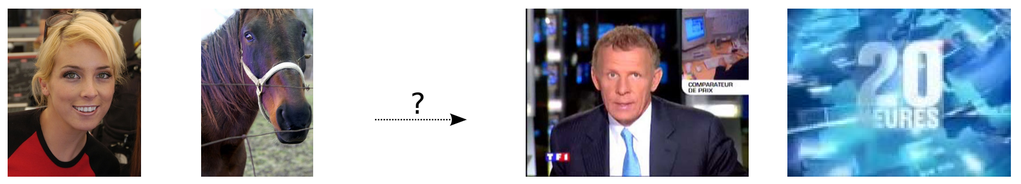
We consider binary classification task:

- X input space, $Y = \{-1, 1\}$ label set
- P_S **source** domain: distribution over $X \times Y$
  D_S marginal distribution over X
- P_T **target** domain: different distribution over $X \times Y$
  D_T marginal distribution over X
- errors of a hypothesis $h : X \to Y$
  · $err_S(h)$, $\widehat{err}_S(h)$ **source** domain errors
  · $err_T(h)$, $\widehat{err}_T(h)$ **target** domain errors
- **Supervised Classification objective**:
  · $h \in \mathcal{H}$ with a **low** $err_S(h)$
- **Domain Adaptation objective**:
  · $h \in \mathcal{H}$ with a **low** $err_T(h)$



For example:

- We have **labeled** images from a **Web image** corpus, *i.e.* $\sim P_S$
- Is there a `Person` in **unlabeled** images from a **Video** corpus, *i.e.* $\sim D_T$?



`Person` `no Person` Is there a `Person` ?

$P_S \neq P_T$

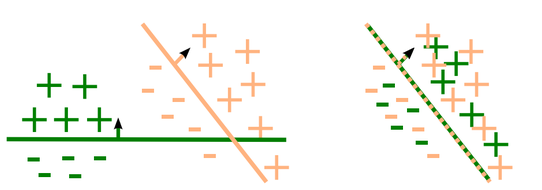
⇒ The Learning distribution is **different** from the Testing distribution
⇒ How can we learn, from the **source domain**, a low-error classifier on the **target domain** ?

Domain Adaptation

Theorem 1 ([2]). *Let $\mathcal{H}$ an hypothesis space. If D_S and D_T are respectively the marginal distributions of source and target instances, then for all $\delta \in]0, 1]$, with probability at least $1 - \delta$, for every $h \in \mathcal{H}$:*

$$err_T(h) \leq err_S(h) + \frac{1}{2} d_{\mathcal{H}\Delta\mathcal{H}}(D_S, D_T) + \nu,$$

*where $d_{\mathcal{H}\Delta\mathcal{H}}(D_S, D_T)$ is the $\mathcal{H}\Delta\mathcal{H}$-**distance** between D_S and D_T and $\nu = err_S(h^*) + err_T(h^*)$, with $h^* = \text{argmin}_{h \in \mathcal{H}}(err_S(h) + err_T(h))$.*



Far domains Close domains

Idea

Build a new projection space to move closer the domains.

Learning with Good Similarity Functions

Definition 1 ([1]). *$K : X \times X \to [-1; 1]$ is an (ϵ, γ, τ)-**good similarity function** for a binary classification problem P if*
(i) A $1 - \epsilon$ probability mass of examples $(\mathbf{x}, y)$ satisfy

$$\mathbb{E}_{(\mathbf{x}', y') \sim P}\left[y y' K(\mathbf{x}, \mathbf{x}') | R(\mathbf{x}') \right] \geq \gamma,$$

*(ii) $Pr_{\mathbf{x}'}[R(\mathbf{x}')] \geq \tau$ (Notation: R set of **reasonable points**).*

Properties

- Generalization of kernels: K may be **not** symmetric and **not** PSD
- A low-error linear classifier can be learned by minimizing the Pb. (**SF**) in the explicit projection space defined by $R = \{\mathbf{x}'_j\}_{j=1}^{d_u}$:

$$\phi^R(.) = \langle K(., \mathbf{x}'_1), \ldots, K(., \mathbf{x}'_{d_u}) \rangle$$

(*Notation:* $\mathcal{H}_{SF}$ the hypothesis space of such classifiers)

Domain Adaptation of Linear Classifiers based on Good Similarity Functions

Building a new projection $\phi^{R'}_{new}$ to move closer D_S and D_T with $\mathcal{C}_{ST}$ a pair set $(\mathbf{x}_s, \mathbf{x}_t) \in U_S \sim D_S \times U_T \sim D_T$ **such that** the deviation of losses of $\mathbf{x}_s$ and $\mathbf{x}_t$ is small

$$\left| \left[1 - y \sum_{j=1}^{d'_u} \alpha_j K(\mathbf{x}_s, \mathbf{x}'_j) \right]_+ - \left[1 - y \sum_{j=1}^{d'_u} \alpha_j K(\mathbf{x}_t, \mathbf{x}'_j) \right]_+ \right| \leq \frac{\left\| ({}^t\phi^{R'}(\mathbf{x}_s) - {}^t\phi^{R'}(\mathbf{x}_t)) \, \text{diag}(\boldsymbol{\alpha}) \right\|_1}{\left\| {}^t\phi^{R'}_{new}(\mathbf{x}_s) - {}^t\phi^{R'}_{new}(\mathbf{x}_t) \right\|_1} \implies \phi^{R'}_{new}(.) = \langle \underbrace{\alpha_1 K(., x'_1)}_{K_{new}(., x'_1)}, \ldots, \underbrace{\alpha_{d_u} K(., x'_{d_u})}_{K_{new}(., x'_{d_u})} \rangle$$

Our global optimization problem

With $\{(\mathbf{x}_i, y_i)\}_{i=1}^{d_l}$ i.i.d. from P_S, $R' = \{\mathbf{x}'_j\}_{j=1}^{d'_u}$ and $\mathcal{C}_{ST}$ a set of pairs $(\mathbf{x}_s, \mathbf{x}_t) \sim D_S \times D_T$.
At iteration l, we build the $\phi^{R'}_{l+1}$ space with the help of $\boldsymbol{\alpha}^l$ inferred by

$$\overbrace{\min_{\boldsymbol{\alpha}^l} \frac{1}{d_l} \sum_{i=1}^{d_l} \left[1 - y_i \sum_{j=1}^{d'_u} \alpha^l_j K_l(\mathbf{x}_i, \mathbf{x}'_j) \right]_+ + \lambda \|\boldsymbol{\alpha}^l\|_1}^{\textbf{(SF)}}$$

$$+\beta \sum_{(\mathbf{x}_s, \mathbf{x}_t) \in \mathcal{C}_{ST}} \|({}^t\phi^{R'}_l(\mathbf{x}_s) - {}^t\phi^{R'}_l(\mathbf{x}_t)) \, \text{diag}(\boldsymbol{\alpha}^l)\|_1 \quad \textbf{(DASF)}$$

Some little results

- **Sparsity Analysis.** With $B_R = \min_{\mathbf{x}'_j \in R} \{ \max_{(\mathbf{x}_s, \mathbf{x}_t) \in \mathcal{C}_{ST}} |K(\mathbf{x}_s, \mathbf{x}'_j) - K(\mathbf{x}_t, \mathbf{x}'_j)| \}$,

$$\|\boldsymbol{\alpha}^*\|_1 \leq \frac{1}{\beta B_R + \lambda}$$

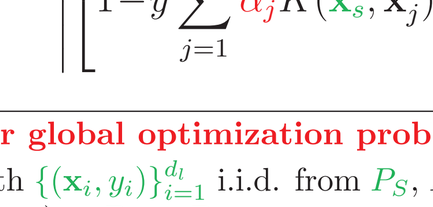
- **Generalization bound.** Following the robustness notion of Xu&Mannor [3], the Problem (**DASF**) is $(\mathbf{2M}_\eta, \frac{\mathbf{N}_\eta}{\beta \mathbf{B_R} + \lambda})$ **robust on** P_S, with $\eta > 0$, M_η is the η-covering number of X and $N_\eta = \max_{\substack{\mathbf{x}_a, \mathbf{x}_b \sim D_S \\ \rho(\mathbf{x}_a, \mathbf{x}_b) \leq \eta}} \|{}^t\phi^R(\mathbf{x}_a) - {}^t\phi^R(\mathbf{x}_b)\|_\infty$. Thus for any $h \in \mathcal{H}_{SF}$, for any $\delta > 0$, with probability at least $1 - \delta$,

$$err_T(h) \leq \widehat{err}_S(h) + \frac{N_\eta}{\beta B_R + \lambda} + \sqrt{\frac{4 M_\eta \ln 2 + 2 \ln \frac{1}{\delta}}{d_l}} + \frac{1}{2} d_{\mathcal{H}\Delta\mathcal{H}}(D_S, D_T) + \nu.$$

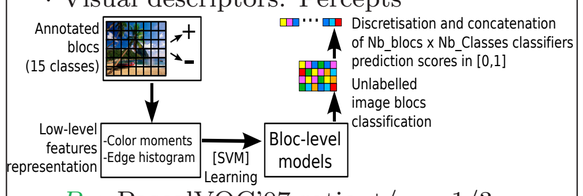
Experiments on Multimedia Indexing

Experimental Setup

- Similarity function:
  K Gaussian kernel, $K^*(., \mathbf{x}'_j) = \frac{K(., \mathbf{x}'_j) - \mu_{\mathbf{x}'_j}}{\sigma_{\mathbf{x}'_j}} \in [-1, 1]$
- Reverse Validation (hyper-parameters tuning)



- Toy problem "inter-twinning moons"
  · 1 P_S, 8 P_T according to 8 rotations
- Image Indexing (according to F-measure)
  · Visual descriptors: Percepts



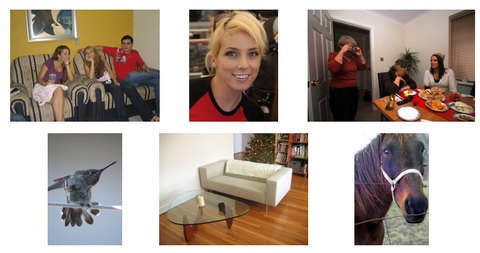
  · P_S: PascalVOC'07 ratio +/− = 1/3
  · P_T: +/− ≠ 1/3: PascalVOC'07 Test
  +/− = 1/3: TrecVid'07

Image Indexing: PascalVOC'07 Vs PascalVOC'07

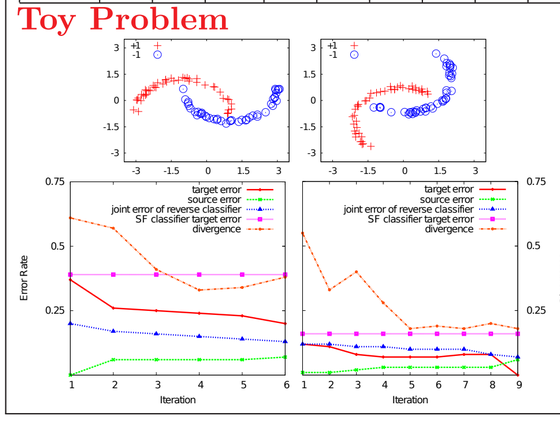
Conc.	bird	boat	bottle *	bus	car	cat	chair	cycle	cow	dining table	dog *	horse	monitor	motor bike	person *	plane	plant	sheep	sofa	train
SVM	0.18	0.29	0.01	0.16	0.28	**0.23**	0.24	0.10	0.15	0.15	0.24	0.31	**0.16**	0.17	0.56	0.34	0.12	0.16	0.16	0.36
SV	867	351	587	476	1096	882	1195	392	681	534	436	761	698	670	951	428	428	261	631	510
SF	0.18	0.27	0.11	0.12	0.34	0.20	0.21	0.10	0.11	0.10	0.18	0.24	0.12	0.17	0.46	0.34	0.13	0.12	0.13	0.20
Reas.	237	203	233	212	185	**178**	241	139	239	**253**	200	**247**	**203**	243	226	**178**	**236**	**128**	224	202
TSVM	0.14	0.14	0.11	0.16	0.37	0.14	0.22	0.13	0.12	0.13	0.22	0.17	0.12	0.12	0.44	0.18	0.10	0.12	0.15	0.19
SV	814	704	718	445	631	779	864	390	888	515	704	828	861	861	1111	585	406	474	866	652
DASVM	0.16	0.22	0.11	0.14	0.37	0.20	0.23	0.14	0.11	0.15	0.22	0.23	0.12	0.14	0.55	0.30	0.12	0.13	0.17	0.28
SV	922	223	295	421	866	1011	1418	706	335	536	**180**	802	668	841	303	356	1434	246	486	407
DASF	**0.20**	**0.32**	**0.12**	**0.17**	**0.38**	**0.23**	**0.26**	**0.16**	**0.16**	**0.16**	**0.25**	**0.32**	**0.16**	**0.18**	**0.58**	**0.35**	**0.15**	**0.20**	**0.18**	**0.42**
Reas.	**50**	**184**	**78**	**94**	**51**	378	**229**	**192**	**203**	372	391	384	287	**239**	**6**	181	293	153	**167**	**75**

Conc.	Average
SVM	0.22
SV	642
SF	0.19
Reas.	210
TSVM	0.17
SV	705
DASVM	0.20
SV	622
DASF	**0.25**
Reas.	**200**

The reasonable points for `Person`:



Toy Problem



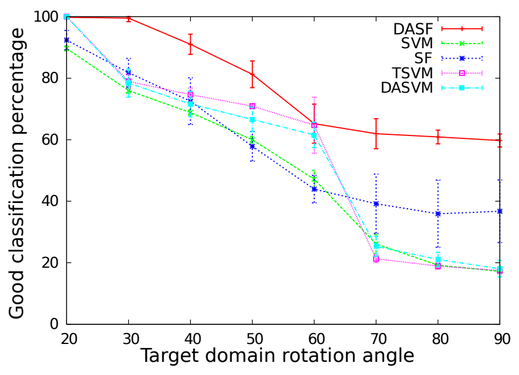


Image Indexing: PascalVOC'07 Vs TrecVid'07

Conc.	boat *	bus *	car *	monitor *	person *	plane *
SVM	0.56	0.25	0.43	0.19	0.52	0.32
SV	351	476	1096	698	951	428
SF	0.49	0.46	0.50	0.34	0.45	0.54
Reas.	214	224	**176**	246	226	178
TSVM	0.56	0.48	0.52	0.37	0.46	0.61
SV	498	535	631	741	1024	259
DASVM	0.52	0.46	**0.55**	0.30	0.54	0.52
SV	202	222	627	523	274	450
DASF	**0.57**	**0.49**	**0.55**	**0.42**	**0.57**	**0.66**
Reas.	**120**	**130**	254	**151**	**19**	**7**

Conc.	Average
SVM	0.38
SV	667
SF	0.46
Reas.	211
TSVM	0.50
SV	615
DASVM	0.48
SV	383
DASF	**0.54**
Reas.	**113**

References

[1] M.-F. Balcan, A. Blum, and N. Srebro. Improved guarantees for learning via similarity functions. In *Proceedings of COLT*, pages 287–298, 2008.

[2] S. Ben-David, J. Blitzer, K. Crammer, A. Kulesza, F. Pereira, and J.W. Vaughan. A theory of learning from different domains. *Machine Learning Journal*, 79(1-2):151–175, 2010.

[3] H. Xu and S. Mannor. Robustness and generalization. In *Proceedings of COLT*, pages 503–515, 2010.